Removing MHD contamination in ECG signals using higher-order statistics and wavelets

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***Abstract*—Cardiovascular Magnetic Resonance (CMR) is nowadays, a useful tool for medical imaging and diagnosis. However, the acquisition of CMR images need to be synchronised with heart motion, a phenomenon called gating. Using the detection of the QRS complex, the electrocardiogram (ECG) signal is a robust and preferred gating method. Moreover, if sedation is used during an MRI exam or if the patient suffers from a cardiovascular disease, the ECG is also required to monitor the heart rate and heart rhythm. However, blood flow in high static magnetic fields induces elevated voltages that disrupt the ECG signal which hinders QRS detection. This is known as the magnetohydrodynamic (MHD effect).**
This paper explores different methods and techniques to confront with the consequences of the MHD effect based on sub-band decomposition using wavelet multiresolution analysis, a real-time QRS detection algorithm exploiting the higher order statistics of the ECG signal and quadratic phase coupling (QPC) inspection. Our analysis was tested in numerous subjects during MRI scans with magnetic field intensities from 1 up to 7 Tesla and enabled promising results for the suppression of the MHD effect in ECG signals during MRI.

I. INTRODUCTION

THE electrocardiogram (ECG) represents the heart electrical activity and is often used during magnetic resonance imaging (MRI) examinations. In MRI of moving organs, such as a beating heart, the ECG is used to compensate the motion of the heart muscle. This is accomplished by synchronising the acquisition of the MRI data with the heart motion, which can be obtained from the ECG signal by QRS detection (gating). The ECG is of vital importance and is often used for cardiovascular monitoring during MRI, especially for patients who are in a critical or unstable condition.
The MHD effect is due to the blood motion in the magnetic environment. In fact, the blood's charged particles flowing in the static magnetic field get deflected by the Lorentz force and as a result a Hall potential is generated across the vessel walls. These voltages, generated by the electrodynamic interactions of the static magnetic field with blood flow, modify the waveform of the recorded ECG signal. The largest magnetically induced voltages occur during the blood ejection phase in the aorta which coincides with the ventricle repolarization (T wave). Thus, the major change observed on the recorded ECG during MRI is an increase of the T wave amplitude.

The first aim of this paper is the development of an MR specific QRS detection algorithm based on higher order statistics (HOS) and wavelet sub-band decomposition. The latter algorithm is evaluated using a 12-lead and 3-lead ECG signal database recorded in various MRI scanners with magnetic field strengths ranging from 1T up to 7T from numerous subjects. The different sub-bands were evaluated quantitatively by measuring the positive predictive value (+P) of the R-wave detection. The sub-bands attained the highest values, were then used to reconstruct the MHD-contaminated signal for further investigation.
The second aim of this paper is the examination of the complexity of the heart dynamics utilizing ECG's power spectra combined with higher order spectral analysis. In our study, we analyze ECG signals using the Fast Fourier Transform (FFT) which is a simple non-parametric algorithm and an efficient method to calculate power spectrum. The power spectrum only provides information about the distribution of the signal's power among its individual frequency components and does not provide any information on the phase relation between them. In order to inspect these relations, the bispectrum, which is the Fourier transform of the third-order correlation of the signal, is used. The bispectrum indicates the cross-correlation between two frequency components in a two-dimensional frequency plot and gives information about the phase coupling between frequencies at f_1, f_2 and f_1+f_2.

II. MATHEMATICAL BACKGROUND

A. Discrete wavelet transform

Discrete wavelet transform decomposes a signal at different scales. Filters of different cut-off frequencies are used for analyzing the signal at different resolution levels. For this purpose, the signal is passed through series of high pass and low pass filters in order to analyze low as well as high frequencies in the signal. At each level, the high pass filter produces a detail information d_n, while the low pass filter associated with scaling function produces coarse approximations A_n. The half band filters produce signals spanning only half the frequency band. This doubles the frequency resolution.
In accordance with Nyquist's rule, if the original signal has a highest frequency f_{max}, it requires a sampling frequency f_s = $2\mathrm{f}_{max}$. Hence, at each decomposition level j, the frequency axis is recursively divided into halves at the ideal cut-off frequencies f_j = $\mathrm{f}_s/2^{j+1}$.

The selection of relevant wavelet is an important task before starting the detection procedure. But there is no universal method suggested to select a particular wavelet. The choice of wavelet depends upon the type of signal to be analyzed and the application. There are several wavelet families like Haar, Daubechies, Biorthogonal, Coiflets, Symlets, Morlet, Mexican Hat, Meyer. The family of biorthogonal wavelets is frequently employed for ECG (PQRST) analysis and is used in this paper.

B. Kurtosis

The kurtosis of a fourth-order stationary, zero-mean, stochastic process $x(t)$ is defined as the fourth-order cumulant for zero-lag. Kurtosis is estimated using a finite-length time-window and its value depends on the length of the sample. Thus, the kurtosis estimate is authorized to exist in a confidence interval, which is conditioned by the probability properties of the estimator. Given a desired confidence interval, the estimator can be framed between two values, depending on the first statistics of the estimator. For the X random variable ($X \in x(t)$) of mean μ and standard deviation σ, the Chebyshev inequality yields a lower bound of the probability that exists inside an interval centered at μ and having a diameter 2ϵ. i.e.,

$$P\{X \in (\mu - \frac{\sigma}{\sqrt{1-q}}, \mu + \frac{\sigma}{\sqrt{1-q}})\} \tag{1}$$

where q=1-(σ^2/ϵ^2), $\epsilon > 0$ and σ^2/ϵ^2 is relatively small. Let $x(n)$ be a zero-mean, N-sample observation from a random variable X. The kurtosis estimate γ_4 of $x(n)$ is given by

$$\gamma_4 = (N-1)\frac{\sum_{n=1}^{N} x(n)^4}{(\sum_{n=1}^{N} x(n)^2)^2} \tag{2}$$

If X is assumed to be Gaussian, then it is easy to show that

$$\mu \approx \frac{6}{N}, s^2 \approx \frac{24}{N} \tag{3}$$

where μ and s are the mean and the standard deviation estimates of γ_4, respectively. Substitution of the expressions (3) in (1) returns

$$P\{\gamma_4 \in I(N,q)\} > q, \tag{4}$$

where

$$I(N,q) = (\frac{6}{N} - \sqrt{\frac{24}{N(1-q)}}, \frac{6}{N} + \sqrt{\frac{24}{N(1-q)}}), \tag{5}$$

concluding that if the kurtosis estimate of a N-sample observation $x(n)$ lies outside I(N,q), then it is legitimate to assume that $x(n)$ does not follow a Gaussian distribution. This concept is transferred to the wavelet sub-band domain as a means to locate the segments of the wavelet coefficients that deviate from Gaussianity, thus detecting the locations of the R-waves sequences. With a simple reconstruction of the selected coefficients, the QRS segments of the ECG signal are feasible.

C. Power spectral analysis

For each signal we obtained the power spectrum using the Fast Fourier Transform (FFT). In most cases, most of the power is distributed among the frequencies in the range of 0-20 Hz. In an ECG signal, pulse frequency ranges from 1 Hz to 1.7 Hz, corresponding to the rhythms of a normal heartbeat. This frequency is called the fundamental frequency of heart dynamics, f_0.

D. Higher order spectral analysis

Since power spectrum is a linear analysis, it cannot give any further understanding on the role of these frequencies or the dynamic relations between them. Thus, we have to do higher order spectral analysis, using bispectra. Bispectral estimation extracts the degree of quadratic phase coupling between individual frequency components of the signal. In order to calculate the bispectrum, the data is divided into N number of segments and their Fourier transforms are calculated. This method, called the direct bispectrum estimation method, expresses bispectrum as

$$b(f_1, f_2) = \sum_{j=1}^{N} X_j(f_1) X_j(f_2) X_j(f_1 + f_2) \tag{6}$$

where N is the number of segments, each with length 1024, in our calculations. X(f_1) and X(f_2) are the discrete-time Fourier transform computed as discrete Fourier transform (DFT) using the FFT algorithm. The bispectrum measures the proportion of the signal energy at any frequency pair that is quadratically phase coupled. Due to inherent symmetries, the bispectrum of a real valued signal can be defined in the triangular region given by $f_1 > 0$; $f_1 \geq f_2$; $f_1 + f_2 \leq f_{max}$, where f_{max} is the Nyquist frequency, the half of the sampling rate. In power spectra of ECG signals analysed, we observe that most of the power is distributed over the frequencies in the range 0-20 Hz. Hence the bispectrum is also calculated for the same range.

III. THE PROPOSED ANALYSIS

A. Frequency sub-band decomposition

The MHD contaminated ECG signal is decomposed onto N levels using the multiresolution decomposition algorithm, based on the classical orthogonal discrete wavelet transform (DWT). The number of scales was fixed according to ECG spectral analysis, taking into account the frequency components of the ECG signal. As for the choice of the analyzing wavelet, a bibliographical study associated with ECG signals analyzed in the wavelet domain has enabled the selection of of the family of biorthogonal wavelets to be tested. The signal wavelet decomposition is shown in (Figure to be included).

B. QRS detection algorithm

The presented QRS detection algorithm utilized the aforementioned properties of kurtosis. The principle of the algorithm is shown in (Figure to be included).
The wavelet coefficient was filtered using a high pass, 5^{th} order Butterworth filter with a cut-off frequency of 3 Hz for amplitude normalization and DC extraction. The kurtosis was then calculated in a sliding window of length L=0.02*f$_s$ and a step width of 1 sample. The length of the R-wave is calculated as the integer part of D=0.2*f$_s$. Next, the coefficient is windowed with a sliding window of L samples. At each window, γ_4 is estimated using (2) and their values correspond to the last frame of the window. Then, a Gaussianity test is performed. Specifically, the confidence intervals from equation (5) are calculated for each window. If the γ_4 calculated for the latter window, lies outside the confidence interval (5), the last frame of this window indicates a possible start of a R-wave.
It is physiologically not possible that a second R-peak occurs 200 ms after another R-peak. This fact was considered by the algorithm.
For our database, the sampling frequency was f_1=1024 Hz resulting in a sliding window of length L=22 samples. The algorithm was implemented using Matlab R2020a.
The metric used for the evaluation of the algorithm is the positive predictive value (+P). These statistical parameters were defined by the ANSI/AAMI EC57 standard and were estimated by

$$+P = \frac{TP}{TP + FP} \tag{7}$$

where TP are the true positives, FP are the false positives. Our approach was to compare the positive predictive values between the wavelet coefficients and select the 2 with the higher score. Then, by summing them up, we reconstruct a new signal in the time domain. In this way, we are able to procced into further analysis by using a signal that has compressed the contamination of the MHD effect. (Table to be included) summarized the QRS detection results of the different wavelet coefficients for the signals inside the 1 Tesla MRI.

C. Power spectrum analysis

Pulse frequency represents the rhythms of a normal heartbeat, ranged from 1 Hz to 1.7 Hz. This frequency is called as the fundamental frequency of heart dynamics f_0.In subjects outside and inside the MRI, this frequency is the main component of the signal and should contain major fraction of the power in the power spectrum. The power spectra of one ECG signal from a subject outside and inside of a 1T MRI are shown in the Figures 1 and 2 as an illustration. It can be seen that for a subject outside the MRI, the power is distributed among the frequencies in the range of 0-20 Hz, whereas in case of MHD contamination the power is distributed among the frequencies in the range of 0-10 Hz.
As we know, ECG waveform can be thought of as a composite signal with many frequency components in addition to the pulse frequency, that arise from various physiological processes. Hence any external factor that contaminates the signal could result in variations in the distribution of power among the component frequencies. Thus suppression of power in a decreased frequency range and redistribution among other frequencies can be taken as an indicator of any external processes that harm the ECG signal, such as MHD.

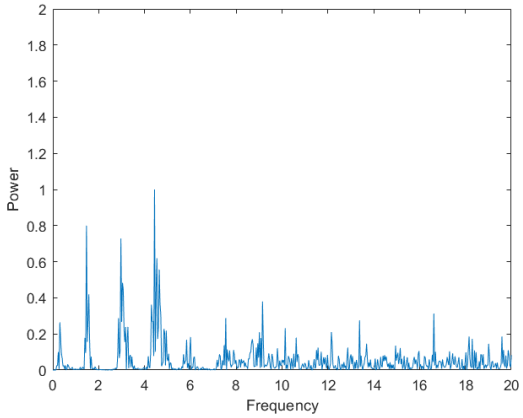

Fig. 1. Power Spectrum of subject outside the 1T MRI

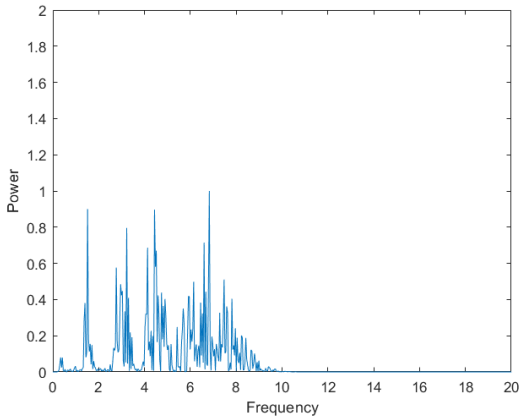

Fig. 2. Power Spectrum of subject inside the 1T MRI

D. Higher order spectral analysis

In order to characterize the underlying dynamics of the heart, we have to do a comprehensive bispectral analysis of the ECG signals. The bispectrum measures the volume of the signal energy at any frequency pair that is quadratically phase coupled. The bispectrum of one ECG signal from a subject outside and inside of a 1T MRI are shown in the Figures 3 and 4 as an illustration.
While the pulse frequency indicates strong phase coupling with other frequencies in the case of non MHD contaminated ECG signals, the number of frequency pairs (f_0,f_1) with significant bispectrum value decreases significantly in the case of MHD contamination. These give interesting MHD specific indications from their relative values.

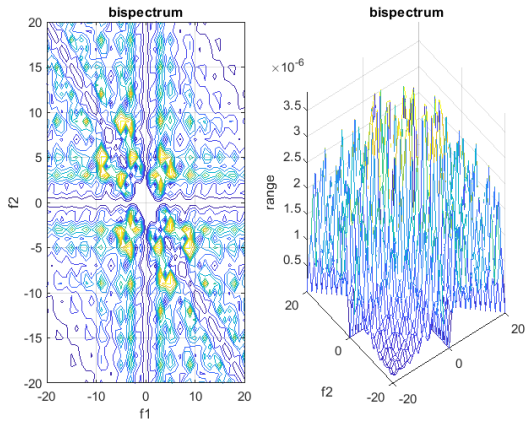

Fig. 3. Bispectrum of subject outside the 1T MRI

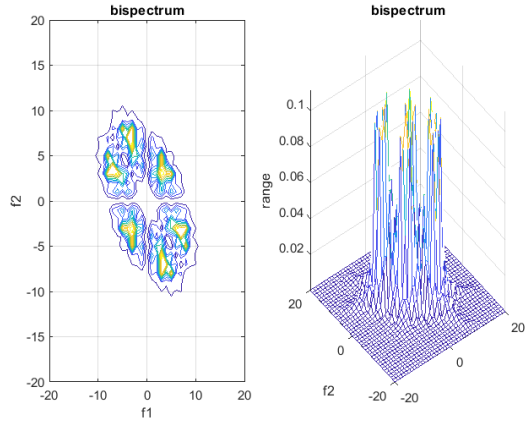

Fig. 4. Bispectrum of subject inside the 1T MRI

For subjects outside the 1T MRI, the n(f_0,f_1) has way larger value. This confirms the nonlinear and chaotic nature and the underlying dynamics of pulse frequency f_0. For signals with MHD contamination, these phenomena are hidden

IV. IMPLEMENTATION ISSUES

A. Experimental database

ECGs were acquired in different MRI scanners with static magnetic field strengths of 1T, 3T and 7T without imaging, i.e. in the absence of the switched gradient and the high frequency magnetic fields. Hence, the ECG signals are only distorted by the MHD effect. For the acquisition of the ECG signals, two different ECG recorders were used: 1) a 12-lead Holter ECG (CardioMem 3000, Getemed AG, Germany) with a sampling rate of 1024 Hz, an input voltage range of ±6mV, a resolution of 12 bit and an analogue bandwidth of 0:05 Hz to 100 Hz and 2) the wireless ECG device of an MRI-conditional patient monitoring system (Tesla M3, MIPM GmbH, Germany) with a sampling rate of 16 kHz (down sampled to 1024 Hz), an input voltage range of +2:4mV and a resolution of 24 bit. The database comprises 43 records from 23 different subjects with an overall length of 203 min. The subjects had an average age of 27:1 ± 3:2 years, an average weight of 73:8± 13:1 kg and a height of 181:7 ± 10:5 cm. The QRS complexes were manually annotated by physicians or ECG experts. No distinction was made between QRS complexes occurring in normal or a disturbed heart rhythm, e. g. caused by ectopic beats.

B. Evaluation Indices

In order to gather the 2 wavelet coefficients to reconstruct the ECG signal, the positive predictive value (+P) was used to compare the coefficients among them. This approach relies on the fact that the MHD increases the amplitude of the T-wave, which is oftenly datected as an R-wave. This way, we are able to locate the coefficients which MHD most contaminates. These coeffients, will have an increased number of false positive (FP) and thus, low positive predictive p value. As we are mostly interested in the number of false positives per coefficient, this metric is the most suitable for the MHD contamination problem.

V. CONCLUSION

A real-time QRS detector based on kurtosis was presented. The algorithm was evaluated using the experimental database described above. The algorithm provides a reliable and accurate QRS detection both for the ECG signal and the wavelet coefficients the signal was decomposed. By selecting the coefficients that MHD contaminates less, we are able to reconstruct the ECG sigal of a subject inside an MRI scanner. This signal compresses the influence of the MHD effect. Hence, it is suited for triggering CMR imaging sequences and patient monitoring during MRI.
The reconstructed signal was then used for spectral analysis, where promising results emerged. More specifically, we can clearly see certain patterns of the MHD contamination, both in the power spectrum and bispectrum domain. These patterns, can be extracted from future studies in order to study the effectiveness of MHD compression algorithms.

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